QUANTIFYING THE IMPACT OF GEOSPATIAL RECOMMENDATIONS: A FIELD EXPERIMENT IN HIGH STREET RETAIL

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Abstract

Once the mainstay of shopping and cultural exchange, many high streets increasingly struggle to compete for their customers' wallets and leisure time against digital shopping. Besides superior convenience and broader assortments, data-driven recommendations of products that fit individual customers' needs are particular assets possessed by online stores. While first recommender systems that leverage the properties of physical environments have been designed and evaluated in shopping malls, their applicability, accuracy, impact, and business value have neither been demonstrated nor evaluated in local high streets. We set out to identify and quantify the impact of geospatial recommendations on high street retail in a large German city center. Having equipped 66 local businesses with more than 120 Bluetooth Low Energy beacons and having distributed a mobile application to 400 customers, we collect geospatial data to trace customer journeys on the high street. In a field experiment, we plan to identify, analyze, and quantify the effects of recommendations in this setting. Our results will provide new data-driven insights into the accuracy, acceptance, impact, and business implications of geospatial recommendations in high street ecosystems.

Keywords: High Street Retail, Customer Experience, Recommender System, Geospatial Data.

1 Introduction

For some hundred years, high streets used to be the primary channel for retail and service provision (Tauber, 1972). Due to the rise of online retail and emerging megatrends (e.g., digitalization, sharing economy) (Seeger and Bick, 2013), the economic importance of high street retail steadily declines, which is reflected in decreasing numbers of visitors in many cities (Bollweg, Lackes, Siepermann, and Weber, 2018; IFH Köln, 2017). Eventually, a decreasing amount of visitors can impede the appearance and attractiveness of high streets since businesses that depend on an active stream of visitors may be forced to close down (Eichholz-Klein et al., 2015). On a general level, the unfolding digitalization profoundly impacts the high street ecosystem by changing the visiting intentions, shopping behavior, and overall habits of citizens, suburbanites, and other visitors (Bollweg, Lackes, Siepermann, and Weber, 2018; Kumar, Anand, and Song, 2017). Different from many large retail conglomerates that have launched online stores to implement omnichannel sales strategies (Brynjolfsson, Hu, and Rahman, 2013), family-owned small and medium-sized enterprise (SME) businesses—often constituting the majority of retail stores in high streets—are laggards regarding digitalizing their stores (Bollweg, Lackes, Siepermann, Sutaj, et al., 2016).

Multi-sided digital community platforms for high streets could be a viable means to make up for this deficiency since they can enable retailers and other service providers to combine their value propositions and offer digital service for improving customer experience on the level of an entire high street (Bartelheimer et al., 2018). These platforms provide a bi-directional digital channel between local customers and local businesses through which digital service is co-created (Barrett, Davidson, and Vargo, 2015).

Inspired by the omnipresence of recommender systems in online retail—supporting customers' decision processes (Ricci, Rokach, and Shapira, 2015) and providing business value for retailers (Lee et al., 2014)—we propose that recommender systems are valuable for customers and retailers in high streets, too. Due to high streets' physical layout as decentralized marketplaces composed of multiple independent businesses, recommender systems have not been applied in high streets, yet. However, digital community platforms seem to provide a suitable technological and organizational foundation for giving recommendations that can influence customers' behavior and decision processes on the level of an entire high street.

Recommendations made in a high street can consider geospatial information such as the locations of businesses, and the customers' physical movements through the high street, which we refer to as trajectories. Thus, recommendations based on geospatial data (henceforth geo-recommendations) can capitalize on both the diversity of businesses on a high street as well as the customers' trajectories, current goals, and context to identify potentially attractive businesses, subject to the distance between customers and stores. If accepted by customers, geo-recommendations could substantially impact customer journeys—time-logical sequences of the discrete service encounters customers have with other actors "along prepurchase, purchase and postpurchase situations" (Homburg, Jozić, and Kuehnl, 2015, p.384). The impact of geo-recommendations on customer journeys have neither been studied nor quantified in high streets before (Gavalas et al., 2014). The purpose of this research-in-progress paper is to outline a research process that will serve to identify and quantify *how geospatial recommendations impact customer journeys in a local high street*. Due to its novelty and unique layout, this endeavor can shed light on the acceptance, use, impact, value, and constraints of geo-recommendations in local high street ecosystems.

2 Theoretical Background

2.1 Recommender Systems

Recommender systems combine tools and techniques that "[produce] individualized recommendations as output or [have] the effect of guiding the user in a personalized way to interesting or useful objects in a large space of possible options" (Burke, 2002). Recommending products, restaurants or promising shopping locations is a long-known social process which has manifested in constructs such as word-of-mouth recommendations, reviews, and surveys and aims at supporting individuals lacking sufficient experience in selecting items deemed most suitable for them (Resnick and Varian, 1997). Digital recommender systems emerged as a class of information systems that provide suggestions for items such as products or Points of Interest (PoI) (Ricci, Rokach, and Shapira, 2015). The underlying decision processes can, among others, consider the properties of the items to recommend (content-based filtering), compare a user to other users (collaborative filtering), and reason upon a user's current situation (Adomavicius and Tuzhilin, 2015). The literature distinguishes different families of recommender systems such as product (e.g., Schafer, J. Konstan, and Riedl, 1999), multimedia (e.g., Albanese et al., 2013; Gomez-Uribe and Hunt, 2016; Hill et al., 1995), news (e.g., Billsus and Pazzani, 1999; Resnick, Iacovou, et al., 1994), and travel recommenders (e.g., Gavalas et al., 2014).

We focus on *geo-recommender systems*, which recommend items in relation to a user's past and current geographical positions (Liu and Wang, 2017). Related approaches exist in the tourism industry, where geo-recommender systems help travelers finding PoI such as sights or hotels (Gavalas et al., 2014). The IT artifacts presented there vary regarding the types of items recommended, additional services offered, and contextual criteria used to derive the recommendations. However, this research stream primarily focuses on technical aspects such as algorithms, system design, route planning, and maximizing recommendation

accuracy (Gavalas et al., 2014; Gorgoglione, Panniello, and Tuzhilin, 2016; Liu and Wang, 2017). Previous studies suggest that the value of a recommender system is not only captured by its underlying algorithm's accuracy but also by the degree of perceived customer experience with regards to the fulfillment of the actual user's needs (Knijnenburg et al., 2012; J. A. Konstan and Riedl, 2012). From a socio-technical perspective, it remains unclear, how geo-recommendations impact users and the environment.
Marketing and Information Systems scholars primarily focus on the use of geo-recommender systems to optimize mobile advertising (Bauer and Strauss, 2016). Recent research uncovered the impact of customers' spatiotemporal contexts on mobile promotion redemption (Luo et al., 2013), found cannibalizing effects (Fong, Fang, and Luo, 2015), showed the superiority of trajectory-based mobile recommendations for promotions (Ghose, Li, and Liu, 2018), and investigated the interplay of recommendation accuracy on customers' purchasing behavior and trust (Gorgoglione, Panniello, and Tuzhilin, 2016). While these studies can inform the design of a geo-recommendation service for local businesses, they are not exploring its impact on customer journeys in high streets due to their focus on maximizing advertising returns through mobile coupons. There is—to the best of our knowledge—no study on how recommendations of nearby businesses impact customer journeys.

2.2 Customer Experience and Customer Journeys in High Streets

To understand the impact of geo-recommendations on customers visiting a high street, we draw from the service-dominant logic (SD-Logic) of marketing (Vargo and Lusch, 2016), customer journey theory (Voorhees et al., 2017), and customer experience theory (Verhoef et al., 2009). SD-Logic substitutes value that comes about through an exchange of goods and services for money (value-in-exchange) with value-in-use that emerges in co-creation between a customer and other actors through the exchange of service—the application of knowledge and skills of a service provider for the benefit of a service customer (Vargo and Lusch, 2016). Customers who visit a high street may interact with service providers, such as retailers or service companies and other customers through various channels such as stores, advertisements, or digital media (Voorhees et al., 2017). The customer's perceived value-in-use of these encounters is reflected by the construct of *customer experience* (Verhoef et al., 2009), which is the "evolvement of a person's sensorial, affective, cognitive, relational and behavioral responses to a [service offering] by living through a journey of touchpoints [...] and continually judging this journey against response thresholds of co-occurring experiences in a person's related environment" (Homburg, Jozić, and Kuehnl, 2015, p.384). As for all service, the value-in-use of visiting a high street is "uniquely and phenomenologically determined" (Vargo and Lusch, 2017, p.47) by the beneficiary, i.e., by the customer. Individual experiences and interactions with other high street actors impact the overall high street customer experience. Vice versa, the overall experience impacts the customer experience on an individual level (Tynan, McKechnie, and Hartley, 2014).
Recently, multi-sided digital community platforms for high streets have been proposed as a means to digitalize and foster the co-creation of customer experience in high streets (Bartelheimer et al., 2018). In particular, these platforms provide customers and retailers with a bi-directional digital channel, enabling service that is based on geospatial data of customers, service providers, and municipal entities. Service is co-created by networks of service providers in the same high street, since improving the potentials for customer experience benefits each constituent and leads to a self-reinforcing process that may strengthen the attractiveness and patronage of high streets. Since digital community platforms for high streets comprise data about local businesses and collect contextual data on customers, we suggest that they can be extended to provide customers with geo-recommendations on the businesses partaking on the platform.

3 Research Approach

We conduct a field experiment to study the impact of geo-recommendations on high street ecosystems (Recker, 2012). This approach corresponds with both recent related work in the research stream (e.g., Ghose, Li, and Liu, 2018) and a recent call for field research by Gavalas et al. (2014), who identified a lack of formal field studies in their survey on mobile recommender systems. Therefore, we aim to study the phenomenon in its real-world context, i.e., the impact of geo-recommendations in a high street, which has not yet been subject to prior research.

The experiment takes place in the city center of Paderborn, which stands as a representative example of about forty cities in Germany. These cities have between 100.000–200.000 residents and feature similar high street structures, which are characterized by a large and diverse set of SME and branches of large retail chains. Thus, there is a sufficiently large number of businesses to give meaningful recommendations. Although the city acts as a regional center for nearby towns and rural areas, it lacks the vibrancy and attraction of metropolises such as Berlin or Cologne, which can hold their own against other shopping channels. So far vacancy rates remain low but local businesses face increasing competition with e-commerce (IFH Köln, 2017). In response, the SME businesses are looking for new value propositions for their customers and express a high degree of openness and cooperation regarding the study.

We split the endeavor into two phases: During the first phase, we equipped the high street with the necessary technology to record and trace individual customer journeys digitally, and thereby we advanced this high street into a physical and at the same time digital ecosystem. In the second phase, we will execute a randomized field experiment by providing a treatment group with geo-recommendations of nearby businesses. An experimental research method with a two-group design is selected to examine cause and effect relationships of geo-recommendations on participants behavior in and perception of the high street (Recker, 2012). Based on the data collected in the field, we will identify, analyze, and quantify the effects of geo-recommendations in the high street setting. The chosen approach enables both inductive data-driven identification of customer behavior as well as deductive research—e.g., hypotheses testing—through "the manipulation and measurement of clearly defined variables, but in a natural setting" (Benbasat, Goldstein, and Mead, 1987, p.370).

4 Geo-Recommendations in High Street Retail

4.1 Digitalization of the High Street Ecosystem

In the first research phase, we digitalized the high street ecosystem and instantiated a digital community platform as a means to collect digital traces of high street customer journeys. Sixty-six local businesses (retailers, restaurants, service providers) and about 400 customers participated in the two-month data collection period, which lasted from November 1st to December 31st, 2018. The sample of test customers consisted of first-year undergraduate students, including both locals with knowledge on the high street and new residents. We acknowledge the sample's limited representative power with regards to demographics and buying power. However, previous studies showed that younger people are more receptive to using digital services in brick and mortar retail in general (Betzing, Niemann, Barann, et al., 2019) and to mobile targeting in particular (Ghose, Li, and Liu, 2018)—rendering them a viable target group.

Customers use a smartphone application to record their high street customer journeys in the form of time-logical sequences of business sightings. We refrained from accessing the GPS sensor due to privacy concerns and limited indoor tracking capabilities. Instead, we equipped the partaking businesses with Bluetooth Low Energy (BLE) beacons that enable indoor and outdoor tracking scenarios (Betzing, 2018). Each business received at least two beacons—one at the entrance and one at the checkout—to track customers passing by and entering the venue. In particular, we record how long a participant remains in-store and whether the participant has bought something (Betzing, Niemann, and Berendes, 2019).

With the technology in place, we can record and retrace individual customer trajectories and store visits in the high street—a valuable data source that in the past has been exclusively available to online shops in the form of click-stream data. During the data collection period, more than 2.000 customer journeys, comprising over 12.000 interactions with the businesses were recorded. The median duration of a high street visit was 62 minutes, which included a median amount of nine interactions with the local businesses.

4.2 Field Experiment with an Instantiated Geo-Recommendation System

In the second research phase, we will field an experiment by giving geo-recommendations to intervene in high street customer journeys. Subsequently, we explain how the geo-recommendation system works, give the experimental design, and sketch our plan to quantify the accuracy and business potential of geo-recommendations in the high street setting.

4.2.1 Recommender Design

We design and instantiate a state-of-the-art geo-recommendation system and train it with the previously collected customer journey data (see Figure 1, *Build Time*). Given an ongoing customer journey trajectory as input, the system's objective is to output geo-recommendations, i.e., to suggest businesses in the vicinity of the user, which are deemed relevant concerning the user's behavior (see Figure 1, *Run Time*).

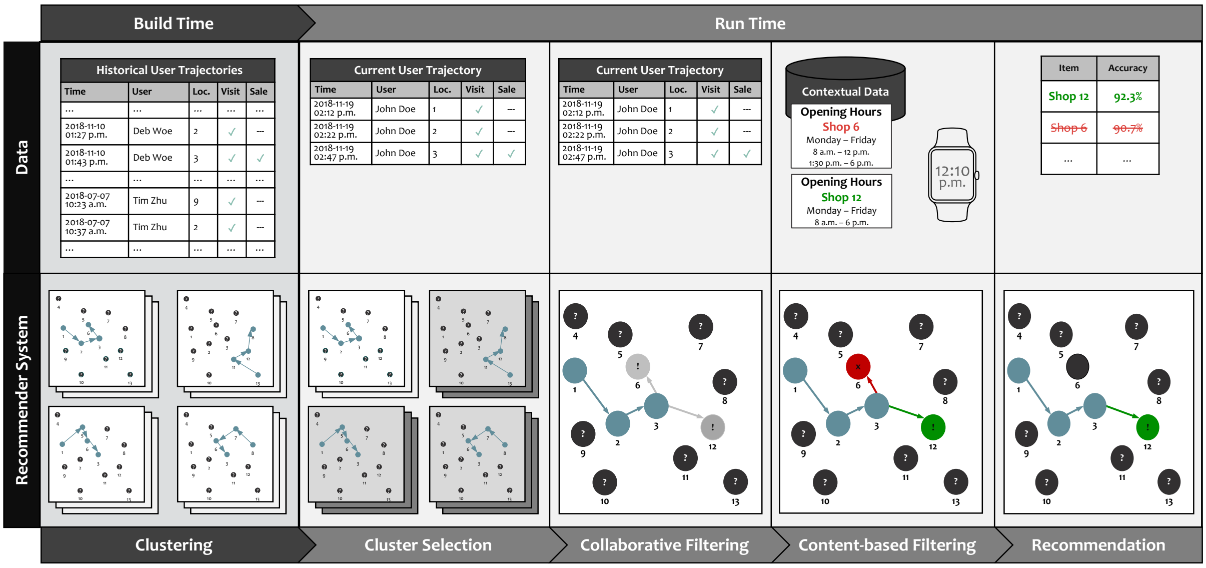


Figure 1: Simplified Recommender System Pipeline and Corresponding Data

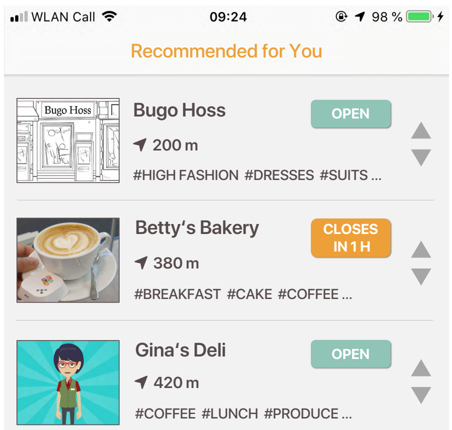
The given trajectories $tr = (p_1, p_2, \ldots, p_n)$ consist of sequences of sampling points $p_i = \langle loc_i, t_i, \ldots \rangle$, which contain information such as the customer's location at/in a business loc_i, a timestamp t_i, and potential further information (e.g., if the user has bought something at the business) (Yuan et al., 2017). The envisioned system is similar to the recent work of Ghose, Li, and Liu (2018), who use graph-based clustering to identify groups of customers in a shopping mall that have similar movement patterns. As opposed to Ghose, Li, and Liu (2018), we are not interested in the overall similarities between customers. Instead, we look at similarities between individual customer journeys, because the same customers might show various behaviors across individual journeys due to different goals when visiting the high street (Walters and Jamil, 2003). Therefore, our system clusters individual trajectories independently of the customers so that journeys within a cluster are similar to each other but dissimilar to the ones not in the group. Informed by Yuan et al. (2017) and Bian et al. (2018) assessments of trajectory-based clustering algorithms, we cluster the data using DBSCAN (density-based spatial clustering of applications with noise) with the longest common sub-sequences (LCSS) distance metric.
Based on the previously learned clusters, the system can categorize a customer's current journey as it commences. Subsequently, collaborative filtering is applied between the ongoing journey and the ones within the selected cluster to calculate a set of potentially relevant businesses (Adomavicius and Tuzhilin, 2015). The set of candidate recommendations is subject to content-based filtering to increase accuracy. As shown in Figure 1, opening hours and holiday indicators are used as filter criteria to prevent recommending

businesses that are currently closed. Additional contextual information such as walking distances between the user and the businesses are taken into account as ranking criteria.
For implementing the geo-recommender system, we selected `LightFM`, which is an industrial grade hybrid recommendation system that has been proven to work well in similar contexts such as online fashion shopping (Kula, 2015). We learn the model using Bayesian Personalized Ranking (BPR) (Rendle et al., 2012), which can deal with missing labels such as customers not having visited a business before (i.e., not visiting a business is not taken as an indicator for disliking it). The overall recommender system pipeline will be incrementally optimized based on the results from the field experiment.

4.2.2 Experimental Design

We will again recruit about 400 participants with demographics comparable to the ones in the first phase and equip them with a mobile application. While the approach would apply to other demographic groups, it would require additional customer journey training data by these groups. Participants of the experiment will be randomly assigned to a control group or a treatment group. The former group is only able to record their trajectories, whereas the latter group will also receive individual geo-recommendations during their high street visits. Invisible to the users, the server-side component will continuously recalculate recommendations for all commencing customer journeys.

(a) Recommendation Push Notification



(b) Recommendations List

Figure 2: Mobile User Interfaces to the Geo-Recommendations

Two modes of treatment delivery take place: First, 20 minutes into the high street visit, the mobile application issues a push notification (see Figure 2a) that suggests the business currently ranked most relevant from the set of recommendations (Xu et al., 2011). If the participant is in an arbitrary store at the calculated delivery time, the notification is held back until he or she returns to public space. We chose this semi-fixed timing to control for any potential bias that could have been introduced by concurrent store visits or randomized timing. Participants leaving the high street within the first 20 minutes do not receive a geo-recommendation. For participants visiting the high street for extended periods of time, the application can issue up to two more push notifications at 30-minute intervals. We limit the number and frequency of notifications to prevent information overload and possibly associated adverse effects (Bauer and Strauss, 2016). Second, at any time during the high street visit, participants can access a pull-based (Xu et al., 2011) mobile recommendation interface that shows the three currently best-fitting businesses from the set of recommendations (see Figure 2b). Due to the novel high street setting, the accuracy of the geo-recommendations cannot be determined beforehand. Therefore, three recommendations instead of a single one are shown to increase the likelihood of providing at least one relevant item (Adomavicius and Tuzhilin, 2015). Within the recommendation list, participants can give feedback by voting the recommendations as relevant or irrelevant (arrows in Figure 2b).

For both groups, we record the customer journeys, including their duration and the number of interactions with businesses. We combine the experiment with a brief post-test survey. After each high street visit, we quantitatively assess the participant's perception of the high street, the course of his or her customer journey, and their intentions to re-visit the high street. Participants who received the treatment will also be surveyed regarding their use of geo-recommendations. Additionally, timestamps of the interventions are logged, and their interactions with the recommendation interface will be recorded (i.e., clicking on recommendation push, notifications, clicking on recommended businesses). All collected measures directly relate to one or more hypotheses that we propose subsequently.

4.2.3 Quantifying the Accuracy of Geo-Recommendations

In line with other studies on recommender systems (Gavalas et al., 2014), we cater for internal validity by determining and quantifying the accuracy of the provided geo-recommendations based on the recorded behavioral data. Geo-recommendations can be understood as an additional touchpoint in the high street ecosystem, which can stimulate digital and personal interaction between the user and the businesses (Nüesch, Alt, and Puschmann, 2015). Following the general aim of PoI recommendations to trigger behavioral responses (Gavalas et al., 2014), we expect customers to visit recommended businesses. Arguably, recommending a business to a local resident might not provide the user with any *new* information, and, in contrast to Ghose, Li, and Liu's (2018) study on mobile coupons, might not increase the user's shopping efficiency. However, in contrast to recommendations for offers and coupons, which especially appeal to utilitarian users (Ghose, Li, and Liu, 2018), our geo-recommendations primarily aim at hedonistic users who prefer strolling the high street (Gavalas et al., 2014) and want to have a digital and at the same time physical high street customer experience (Betzing, Beverungen, and Becker, 2018). We maintain that even recommendations for known locations can give impulses to spontaneously re-visit them (Babin, Darden, and Griffin, 1994). Consequently, the system can recommend both businesses already visited by the customer in a previous journey and those that are unknown, yet. We assess whether previous knowledge on the recommended business impacts the customers' behavioral response, i.e., if recommendations lead to discover unknown businesses and/or to re-visit known ones (Fleder and Hosanagar, 2007). Against this backdrop, we propose our first hypotheses:
H1a: *Geo-recommendations positively impact customers to visit previously unknown businesses.*
H1b: *Geo-recommendations positively impact customers to re-visit previously known businesses.*
Ghose et al. (2018) recently showed that trajectory-based mobile advertising could nudge users towards changing their shopping behavior. Similarly, we expect users to change their planned trajectories in the high street in order to visit the recommended businesses. They might even use this new trajectory to make other (previously unplanned) visits to businesses on the way. Intuitively, one may expect geo-recommendations to extend the duration of and distance traversed in a customer journey due to visiting the recommended businesses. However, recommendations are known to yield a functional value due to easing information search (Ricci, Rokach, and Shapira, 2015). If a recommended business fulfills the customer's needs, he or she may even have efficiency gains since it eliminates the search process to find an adequate business (Ghose, Li, and Liu, 2018). Consequently, we cannot make assumptions on the direction of the effect. We state our second set of hypotheses as follows:
H2: *Geo-Recommendations impact the duration of high street customer journeys.*
H3: *Geo-Recommendations impact the number of businesses visited in high street customer journeys.*

4.2.4 Quantifying the Business Potential of Geo-Recommendations

Beyond quantifying the impact of geo-recommendations on customers' behavior, we also expect geo-recommendations to positively impact the customers' perception of the high street as a whole.
Geo-recommendations can support customers in learning about the latest trends (Tauber, 1972), explore new and unknown stores on the high street (Jarboe and McDaniel, 1987), and conduct "adventure shopping" (Arnold and Reynolds, 2003), all of which are known to yield a positive value-in-use (Arnold and

Reynolds, 2003). In particular, a feeling of joy from making a serendipitous discovery can create hedonic value-in-use (Babin, Darden, and Griffin, 1994; Bellotti et al., 2008), which may then affect the perceived value-in-use of the high street (visit) as a whole (Tynan, McKechnie, and Hartley, 2014). High street businesses often are geographically dispersed, and customers may walk by relevant businesses without recognizing them. Geo-recommendations may increase customers' awareness of what the high street has to offer, and thus, may increase the perceived attractiveness of the high street (Um, Chon, and Ro, 2006). Further, as users tend to evaluate their current experience in relation to previous experiences (Betzing, Beverungen, and Becker, 2018), value-in-use and attractiveness perceived during the current high street visit may affect future behavior. Perceived value-in-use and perceived attractiveness are known concepts to explain customers' re-visit intentions of a high street (Um, Chon, and Ro, 2006). Additionally, positive customer experience is known to impact "satisfaction, trust, [and] re-visit intention" (McLean, Al-Nabhani, and Wilson, 2018, p.326). To go beyond educated assumptions, we sketch a third set of hypotheses that will allow a thorough empirical evaluation of the above-stated premises:

H4: *Geo-recommendations positively impact customers' perceived value-in-use of a high street.*

H5: *Geo-recommendations positively impact customers' perceived attractiveness of a high street.*

H6a: *A higher perceived value-in-use of a high street positively impacts customers' re-visit intentions.*

H6b: *A higher perceived attractiveness of a high street positively impacts customers' re-visit intentions.*

However, deriving business potentials of geo-recommendations for high streets as a whole is hardly possible without taking multiple consumer moderators from customer experience theory into account (Verhoef et al., 2009): (1) The type of shopping trip respectively the customer journey goal drives the customer's need for recommendations (Walters and Jamil, 2003). Utilitarian customers that have a clear goal such as buying a particular product (Ghose, Li, and Liu, 2018) may not respond in the same way to geo-recommendations than a hedonistically motivated customer who wants to window shop in his or her leisure time (Homburg, Jozić, and Kuehnl, 2015). (2) The social environment that is made by the persons who accompany the customer during his or her trip may constrain the relevance of recommendations (Verhoef et al., 2009). (3) Socio-demographic factors such as age, gender, and technology affinity may further impact the use of a geo-recommendation system (Gavalas et al., 2014). Data on all moderators will be collected during the field experiment, which allows us to control for them.

5 Conclusion

Against the backdrop of diminishing customer frequencies in many high streets, we set out to identify and quantify the impact of digital geo-recommendations on a high street ecosystem. We digitalized a German high street and collected real-world customer journey data—an asset that allows us to build and train a geo-recommendation system. In a field experiment in the same high street, we will intervene in customer journeys by giving geo-recommendations and record customers' responses. The paper provides sets of hypotheses regarding the quantitative impact of geo-recommendations on customer behavior and the perceived value-in-use of the high street as a whole. These hypotheses can only be tested in situ, which has not been done before. We gain novel insights by identifying the applicability, limitations, and effects of geo-recommendations for high streets and even quantify them with collected data. Thereby, we contribute to the research streams on recommender systems, high street retail, and customer experience. We are confident that augmenting customer journeys in high streets with geo-recommendations generates a value-in-use for both customers and businesses, and that providing a geo-recommendation service might eventually contribute towards strengthening the high street's competitive position in channel selection.

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